Efficient Learning for Discriminative Segmentation with Supermodular Losses

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- loss augmented inference
- ADMM

Abstract

Several non-modular loss functions have been considered in the context of image segmentation. These loss functions do not necessarily have the same structure as the segmentation inference algorithm, and in general, we may have to resort to generic submodular minimization algorithms for loss augmented inference. Although these come with polynomial time guarantees, they are not practical to apply to image scale data. In this work, we first propose a supermodular loss function that is itself optimizable with graph cuts. It counts the number of incorrect pixels plus the number of pairs of neighboring pixels that both have incorrect labels. Maximization of this loss function is equivalent to a supermodular function maximization problem. It emphasizes the importance of correctly predicting adjacent groups of pixels, e.g. those present in thin structures more than one pixel wide. The loss function maps to a set function by considering the set of pixels that are incorrectly labeled, while the inference maps to a set function by considering the set of pixels that are labeled as foreground.The incorporation in a joint loss-augmented inference leads to non-submodular potentials. We therefore use the alternating direction method of multipliers (ADMM) based decomposition strategy. It consists of alternatively optimizing the loss function and performing Maximum a Posteriori (MAP) inference, with each process augmented by a quadratic term enforcing the labeling determined by each to converge to the optimum of the sum. In general, we simply need task-specific solvers for two subproblems, which need not use a single graph cut algorithm and can therefore exploit any available structure. In this way, we gain computational efficiency, making new choices of loss functions practical, while simultaneously making the inference algorithm employed during training closer to the test time procedure. We show improvement both in accuracy and computational performance on the Microsoft Research GrabCut database and a brain structure segmentation task. We show that: (i) our proposed splitting strategy is orders of magnitude faster than the minimum norm point algorithm; (ii) our strategy yields results nearly identical to a LP-relaxation while being much faster in practice; and (iii) training with the same supermodular loss as during test time yields better performance. Qualitative segmentation results show that our 8-connected loss achieves better performance on the foreground/background boundary, as well as on elongated structures of the foreground object, such as the head and legs, especially when the appearance of the foreground is similar to the background. We empirically validate the use of a supermodular loss during training and the improved computational properties of the proposed ADMM approach over the Fujishige-Wolfe minimum norm point algorithm.We envision that this can be of use in a wide range of application settings, and an open source general purpose toolbox for this efficient segmentation framework with supermodular losses is available for download from https://github.com/yjq8812/efficientSegmentation.

Note: This work is accepted at BMVC2016 for oral presentation. Full text of this work is available at [1].

[1] Jiaqian Yu and Matthew B. Blaschko. Efficient learning for discriminative segmentation with supermodular losses. In *Proceedings of the British Machine Vision Conference*. BMVA Press, 2016.